Artificial Intelligence in Dynamic Compaction for Geotechnical Site Characterization

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ABSTRACT

We present a novel method using four artificial intelligence (AI) algorithms to anticipate the cumulative degree of soil compaction (CDSC) after dynamic compaction (DC). Four AI algorithms adopted in this study include support vector regression SVR, artificial neural network (ANN), random forest (RF), and gradient boosting machine (GBM). Input variables for AI algorithms involve the average SPT N-value before dynamic compaction, cumulative applied energy normalized with a cross-sectional area of tamper, and the number of the tamper drops. Apart from cross-validation with a testing set, additional in situ test data compiled from a different section within the studied site are used to estimate the generalized capacity of the AI models. In addition, we conduct out-of-distribution analyses for the four AI algorithms in view of parametric studies. The CDSC prediction performance for the four AI models results in high prediction metrics of accuracy with the r^2 higher than 0.9 for the testing scenario while the r^2 of the other AI models is more than 0.9 when out-of-sample data are considered except for the GBM. The ANN seems to be the best model as the parametric study considers out-of-distribution data and suggests a strong relationship between input variables and CDSC that is more coherent with engineering principles for DC. Finally, the ANN model can be utilized to develop a mathematical model for CDSC prediction.

Keywords: Artificial intelligence; Cumulative degree of soil compaction; Dynamic compaction; Standard penetration test; Machine learning.

1. Introduction

Dynamic compaction DC is an ancient ground improvement method involving heavy tamping to densify loose soils, historically used by Romans, Chinese, and Americans (Kramer and Holtz 1991; Thevanayagam et al. 2006). It is effective for loose sand deposits like alluvial, coastal, or sedimentary fills. Design relies on empirical correlations and charts, estimating depth of improvement and crater depths (Menard and Broise 1975; Lukas 1995). Conventional models lack consideration for site-specific factors and provide depth of impact rather than soil compaction degree. In situ tests and computational studies address these limitations, with emerging interest in AI for dynamic compaction design due to its capability to analyze nonlinear soil behavior.

Artificial intelligence, particularly machine learning, has shown promise in various geotechnical applications. Algorithms like artificial neural networks ANN, support vector machine SVM, and random forest RF have been successful in predicting various geotechnical parameters. Previous studies demonstrate the superiority of AI over traditional methods in prediction accuracy (Shahin and Broise 2008).

In this study, four AI algorithms ANN, SVR, GBM, RF were applied to predict soil compaction degree induced by dynamic compaction. Input variables include SPT N data, normalized cumulative applied energy (E_a), and number of tamper drops (N_{drops}), while cumulative degree of soil compaction (CDSC) is the target. Models were trained, tested, and cross-validated, with ANN showing the most robust performance. High prediction accuracy (r^2 > 0.9) was achieved, even with out-of-sample data, suggesting AI's potential for precise dynamic compaction design.

2. Study Area and Data Available

2.1. Site description

Limited capacity led to land reclamation along Ulsan's southeastern coast for oil storage and harbor construction (Fig. 1). The site, mainly coarse-grained soil with a water table about 2 meters below sea level, had low SPT N-values (2-32, average 14), indicating weak bearing strength. Dynamic compaction, using a 22.5-ton tamper dropped from 20 meters with a base area of 2.27 m², significantly improved soil strength, raising SPT N-values to 30-43 post-compaction.

2.2. Data pre-processing and correlation

Data used in this study were sourced from sections 3 and 9 of the sites (Fig. 1). The input variables used for prediction of the cumulative degree of soil compaction CDSC involve the average SPT N before the dynamic compaction, N_{ini}, the number of the tamper drops, N_{drops}, and cumulative applied energy normalized with a cross-sectional area of tamper, E_a. Calculation of the applied energy E_a uses the following equation (Lukas 1995):

$$E_a = \frac{N_{drops} \cdot W_t \cdot H_{drop}}{A_e \cdot A_t} \quad (1)$$

where W_t = weight of tamper, H_{drop} = height for the tamper drop, A_e = influence area of each impact point (i.e., $A_e = s^2$; s = spacing between tamper drops), and A_t = cross-sectional area of tamper. Equation (1) indicates that the applied energy E_a decreases with a larger tamper cross-sectional area (note: this study uses a single tamper). The cumulative degree of soil compaction CDSC is calculated using the N_{ini} and N_{final} information per test location as follows:

$$CDSC = \frac{N_{final} - N_{ini}}{N_{ini}} \quad (2)$$

where N_{ini} is the average SPT N before dynamic compaction and N_{final} is the average SPT N after dynamic compaction. The predictive model for estimating the CDSC is trained and tested with data obtained from only section 9, and then each AI model is further cross-validated with data from section 3.

The ANN model used in this research is modeled with a sigmoid activation function which is asymptotic to 0 and 1. Based on these limits of the sigmoid function, the data for the ANN is scaled within a range of 0.1 to 0.9 using the equation below:

$$I_{scaled} = 0.1 + \frac{I_{unscaled} - I_{min}}{I_{max} - I_{min}} \cdot (0.9 - 0.1) \quad (3)$$

where I_{max} and I_{min} are the maximum and minimum values for the unscaled dataset. The scaling of the data ensures early convergence at a very low error; in general, it leads to an efficient learning process. After the training and testing process, the predicted variables are unscaled to their original values. Note that the other AI models do not require data pre-processing as they can be trained using unscaled or raw data (Vapnik 1999; Breiman 2001).

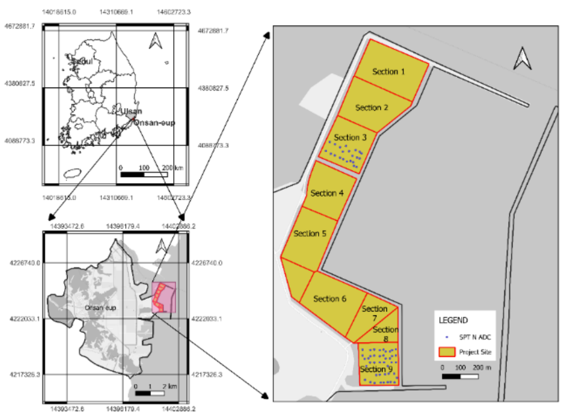


Figure 1. Site location map indicating the study areas

Fig. 2 shows Spearman's rank correlation heatmap and Table 1 shows correlation classifications based on absolute r_s values of feature variables to the target. The results of r_s suggest that N_{ini} and N_{drops} are moderately correlated with CDSC with r_s values of -0.53 and 0.46, respectively while the N_{drops} parameter is strongly correlated with CDSC with r_s of 0.75 (see Figure 2 and Table 1) because the implementation of DC reveals that the ground improvements generated by dynamic compaction increase gradually with the increasing number of tamper drops.

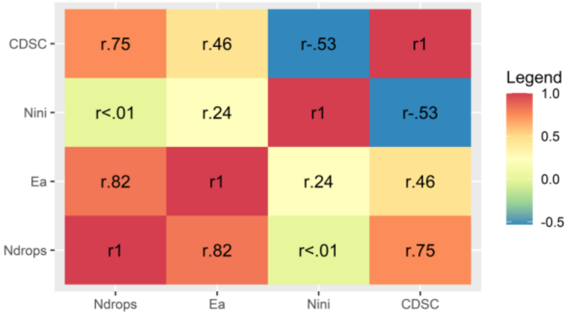


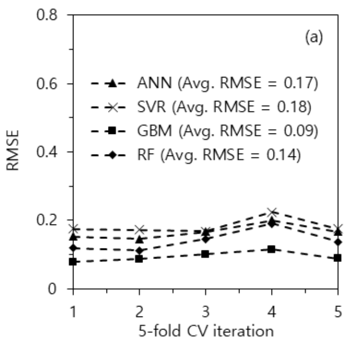
Figure 2. Spearman's rank correlation coefficient heatmap for input parameters and the target variable.

3. Results

This section presents the results for the cumulative degree of soil compaction CDSC predicted from the four AI models (i.e., artificial neural network ANN, support vector regression SVR model, gradient boosting machine GBM modeling, random forest RF) and their cross-validations CV and comparison. In particular, an optimal AI model is selected and assessed with a parametric sensitivity analysis based on the CDSC prediction performance assessed with metrics of accuracy MOA and parametric study.

3.1. Data division

Fig. 3 illustrates RMSE values for predicting cumulative degree of soil compaction (CDSC) using iterative training and testing with data from Section 9, and validation with data from Section 3. In Figure 3(a), all AI models demonstrate successful learning with minor estimation errors (RMSE < 0.2). GBM and RF exhibit better performance compared to ANN and SVR in training data prediction. Ensemble models like GBM often outperform others due to their boosting method. Figure 3(b) shows low RMSE values (< 0.2) for all models in testing, with GBM performing the best. In Figure 3(c), ANN and SVR show higher errors, possibly due to data similarities with training data. RF has the lowest average RMSE, outperforming others. Models from iteration 3 are selected for further analysis due to consistently low RMSE values.



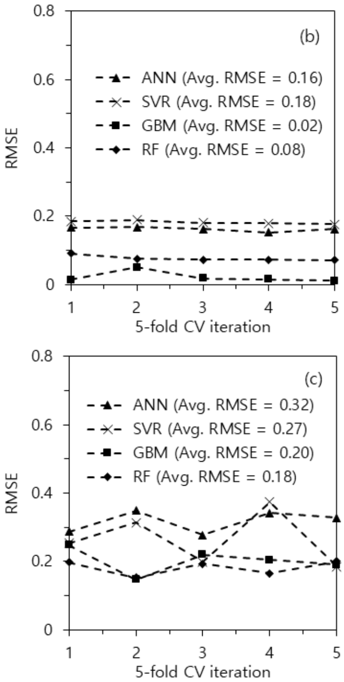


Figure 3. Root mean square error RMSE values for the cumulative degree of soil compaction CDSC predicted using (a) Training set with data in Section 9, (b) testing set with data in Section 9, and (c) validation with with data in Section 3.

3.2. Performance evaluation of AI predictions

This study focuses on using measures of accuracy (MOA) to assess the performance of four AI models for predicting CDSC. Evaluation metrics include root mean square error (RMSE), coefficient of determination (r2), and mean absolute error (MAE). Low MAE and RMSE, along with high r2 values, signify effective CDSC prediction by AI models. Cross-validation is conducted for both the training and testing datasets in Section 9, as well as the data in Section 3.

3.2.1. Training

Training. For each AI model employed in this study, the cross-validation plots based on the training set are displayed in Fig. 4. Fig. 4 shows that the MOA involves a high r2 = 1, and low MAE = 0.01 and RMSE = 0.02 for GBM and a high r2 = 0.98 and a low MAE = 0.05 and RMSE = 0.07 for RF. Both GBM and RF show relatively low errors in terms of MAE and RMSE and a high coefficient of determination due to the ensemble learning technique, which is popularly known for its high prediction accuracy in comparison to ANN and SVR (Opitz and Maclin 1999; Polikar 2006). Although ANN indicates relatively low prediction performance in comparison to GBM and RF, the MOA for ANN involves low errors of MAE = 0.11 and RMSE = 0.16 and a high coefficient of determination, r^2 = 0.91. These MOA values for ANN support that the trained ANN efficiently mapped the relationship between the inputs and the output. SVR results in a high r^2 = 0.89, a low MAE = 0.14, and a low RMSE = 0.18 (Figure 4b). These MOA values result from its learning method, which accommodates a degree of error to improve the generalization ability of the SVR model (Chow et al. 1992; Chik et al. 2014). The evaluation MOA for the prediction of CDSC by the four AI models using the training set suggests that GBM performs the best followed by RF, ANN, and SVR the least.

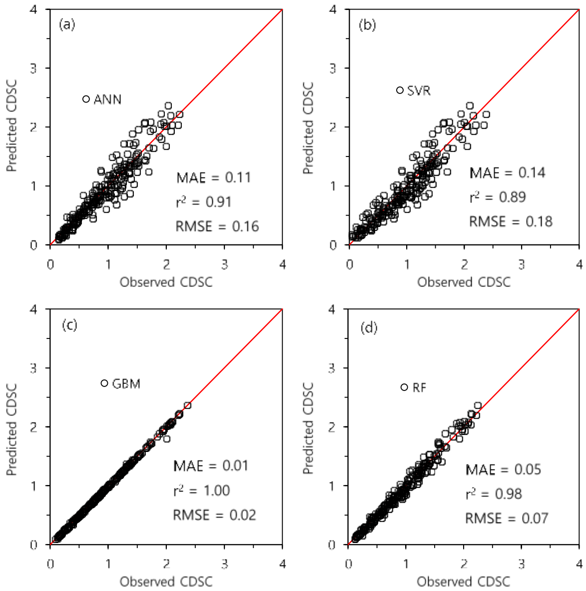


Figure 4. Cross-validation plots from ML CDSC predictions using training set with data in Section 9: (a) ANN, (b) SVR, (c) GBM, and (d) RF.

3.2.2. Testing

Fig. 5 displays cross-validation (CV) plots for the four AI models using the testing subset, entirely unknown to the trained model. Evaluation of CDSC prediction performance based on measures of accuracy (MOA) reveals GBM as the top performer, followed by RF, ANN, and SVR. GBM and RF exhibit high prediction performance with high r^2 and low errors (MAE and RMSE in Figure 5c and 5d). Their MOA values for the testing dataset indicate robust prediction and high generalization ability. GBM results suggest successful training without significant overfitting.

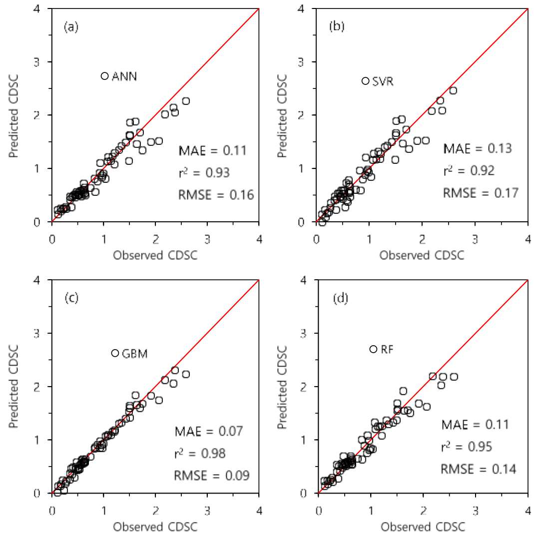


Figure 5. Cross-validation plots from the ML CDSC predictions using testing set with data in Section 9: (a) ANN, (b) SVR, (c) GBM, and (d) RF.

3.2.3. Validation

Fig. 6 displays cross-validation plots utilizing the trained AI models and data from Section 3. Evaluation of measures of accuracy (MOA) for the four AI models indicates satisfactory and reliable CDSC prediction performance, a typical characteristic of AI models. While SVR and RF yield similar results, ANN exhibits a higher r2 compared to GBM, although GBM demonstrates lower error values than ANN. SVR's improved performance with Section 3 data may be attributed to its ability to tolerate estimation errors through the hyperparameter "cost" (C). By selecting a low cost, SVR accommodates prediction errors during training, enhancing its generalization ability when tested on validation datasets. MOA values for CDSC prediction performance obtained by the four AI models across training, testing, and validation datasets suggest difficulty in identifying the best model due to highly comparable performance across all scenarios. Further investigation is necessary to determine the optimal model in subsequent subsections.

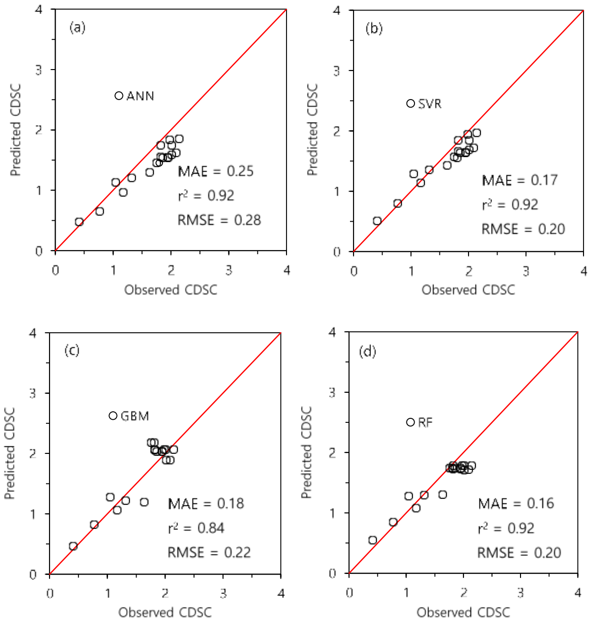


Figure 6. Cross-validation plots from the ML CDSC predicted using data in Section 3. (a) ANN, (b) SVR, (c) GBM, and (d) RF.

4. ANN Model Deductions

4.1. ANN model topology

Fig. 7 depicts the architecture of the ANN model used in this study, featuring three nodes in the input layer, two nodes in the hidden layer (H1 and H2), and an output layer representing CDSC. The ANN method constructs a network by incorporating biases and weights to the input and hidden layers, influencing the output layer. A 5-fold cross-validation process determines the optimal weights, biases, and number of hidden layer nodes for this ANN topology. The architecture visualizes the weights assigned to each variable, with positive weights depicted by black lines and negative weights by grey lines. The thickness of the lines indicates the magnitude of the weights. Analysis of the architecture reveals the significance of N_{drops} and N_{ini} in CDSC prediction, while E_a contributes minimally. Variable importance analyses further quantify each input parameter's actual contribution to the ANN-based CDSC prediction.

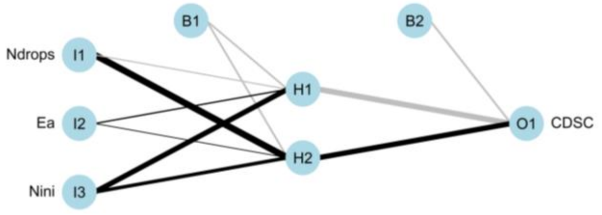


Figure 7. ANN model architecture used for CDSC prediction model.

4.2. Input variable importance

The Garson model, utilized to evaluate input variable importance in the ANN model, employs absolute scale values derived from the deconstruction of optimal weights. This algorithm scales the importance of input parameters, expressing their contribution out of a total value of 1. In Fig. 8, N_{ini} ranks as the most influential variable for CDSC predictions, followed by N_{drops} and E_a. A low N_{ini} value reflects location characteristics and is particularly responsive to dynamic compaction (DC). Notably, under constant A_e, A_t, N_{drop}, and H_{drop} conditions, E_a increases with higher tamper weight, leading to higher CDSC. Therefore, the importance rank could change with the use of multiple tampers with different weights.

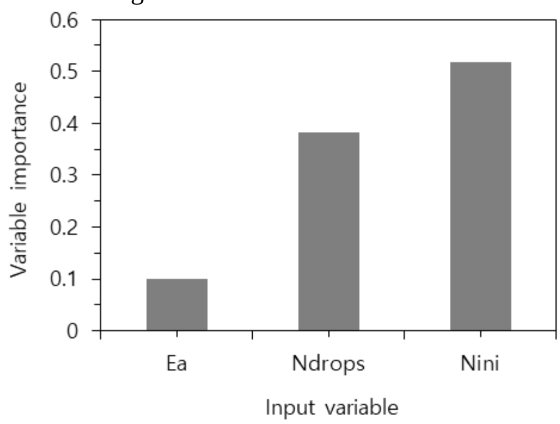


Figure 8. Input parameter importance for ANN using Garson's model.

4.3. Input parameter sensitivity

This study involves parametric sensitivity analysis (PSA) of input variables for the ANN model to assess their impact on predicting the cumulative degree of soil compaction (CDSC). The analysis divides input variables such as N_{drops}, E_a, and N_{ini} into six splits based on data distribution, ranging from minimum to maximum quantiles. Each split corresponds to a different value range, with "split 1" representing the minimum value and "split 6" representing the maximum value. The analysis varies a single input variable of interest from splits 1 to 6 while keeping the other two variables constant across their entire range. For instance, in Fig. 9, when the X-axis shows quantile 0, both E_a and N_{ini} remain at their minimum values (split 1), while N_{drops} varies from split 1 to split 6.

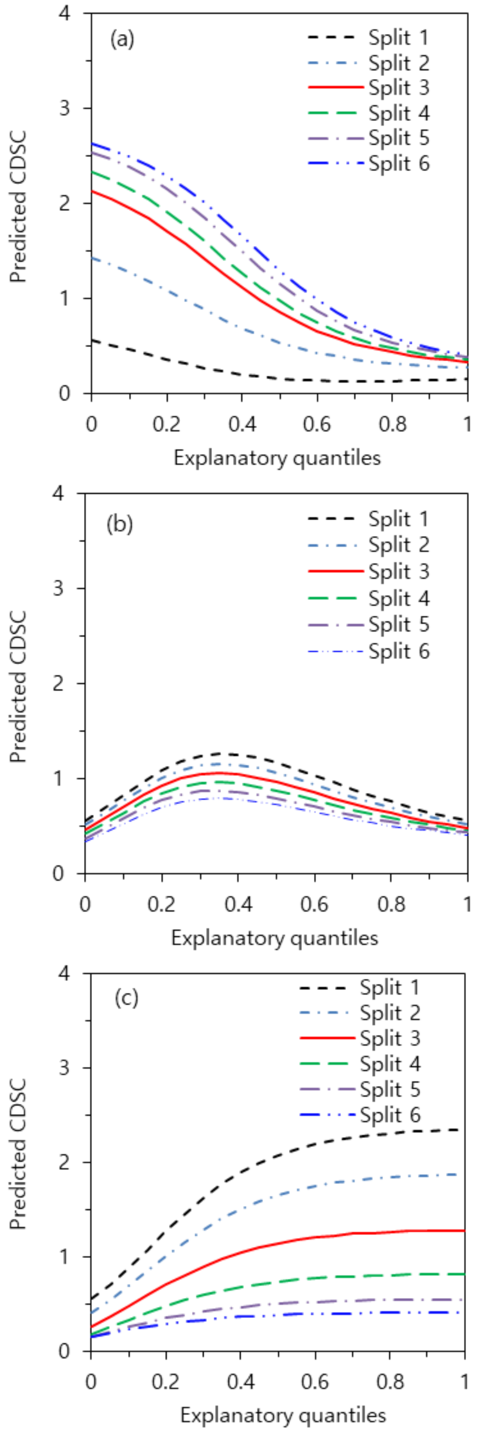


Figure 9. Parameter sensitivity analysis plots for the optimal ANN model: (a) N_{drops}, (b) E_a, and (c) N_{ini}.

In Fig. 9(a), the parametric sensitivity analysis (PSA) for N_{drops} reveals a correlation between CDSC and the increasing number of tamper drops (splits 1-to-6) while other variables remain constant. This highlights the significance of the lowest average SPT N before DC, particularly as the number of tamper drops increases, indicating substantial ground improvement (Lukas 1995). However, CDSC gradually declines across all N_{drops} splits as explanatory quantiles rise from minimum to maximum values, attributed to increasing N_{ini} reflecting denser soil layers. At low explanatory quantiles, CDSC tends to approach low values for all N_{drops} splits, suggesting minimal ground improvement in very dense soils due to dynamic compaction (Chik et al. 2014).

In Fig. 9(b), the PSA for E_a shows that split 1 (maximum Ea) results in the highest CDSC across all explanatory quantiles. There's a transition of CDSC, with peak CDSC occurring at explanatory quantiles = 0.3-to-0.4. This indicates inefficiency of dynamic compaction for very loose and dense soil layers due to soil dilation or energy absorption rather than transfer. At the lowest explanatory quantile (maximum N_{drops} and N_{ini}), predicted CDSC reaches a low asymptote across all splits, suggesting difficulty in further densification of dense soil layers (Das 2015). Conversely, at the highest explanatory quantile (maximum N_{drops} and N_{ini}), dynamic compaction energy may dissipate in other forms without significant soil densification. The narrow range of CDSC values with 6 splits indicates ANN-based CDSC prediction's low sensitivity to changes in E_a, aligning with practical dynamic compaction processes.

In Fig. 9(c), the PSA for N_{ini} illustrates a notable increase in CDSC with rising explanatory quantiles towards maximum N_{drops} and E_a, with split 1 (smallest N_{ini}) resulting in the highest CDSC. Dynamic compaction's effect on very loose soils with low N_{ini} appears significant up to explanatory quantiles of 0.4, beyond which the effect diminishes. This suggests a threshold in dynamic compaction where small gains are achieved, consistent with practical DC processes.

5. Summary and Conclusions

Four commonly used artificial intelligence (AI) models, namely ANN, SVR, GBM, and RF, were assessed in this study for predicting soil compaction induced by dynamic compaction (DC). An equation based on the ANN model was developed to predict CDSC. Overall, the AI models demonstrated robustness in forecasting DC-induced ground improvement, with ANN emerging as the best model. The optimal ANN accurately captured soil compaction degree considering energy input, tamper drops, and subsurface conditions (Nini). Cross-validation using the test set and out-of-sample data from Section 3 confirmed good CDSC prediction accuracy for all AI models, particularly the optimal ANN. Sensitivity analysis revealed Nini and Ndrops as the most influential parameters, while Ea had the least impact. The ANN model remained reliable and robust across various input parameter combinations, yielding rational CDSC estimations. The innovative AI technique complements rather than replaces standard design processes, enhancing smart DC design solutions.

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